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Simulated Annealing Approach Applied to the Energy Resource Management Considering Demand Response for Electric Vehicle

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***Abstract*—The aggregation and management of Distributed Energy Resources (DERs) by an Virtual Power Players (VPP) is an important task in a smart grid context. The Energy Resource Management (ERM) of theses DERs can become a hard and complex optimization problem. The large integration of several DERs, including Electric Vehicles (EVs), may lead to a scenario in which the VPP needs several hours to have a solution for the ERM problem. This is the reason why it is necessary to use metaheuristic methodologies to come up with a good solution with a reasonable amount of time. The presented paper proposes a Simulated Annealing (SA) approach to determine the ERM considering an intensive use of DERs, mainly EVs. In this paper, the possibility to apply Demand Response (DR) programs to the EVs is considered. Moreover, a trip reduce DR program is implemented. The SA methodology is tested on a 32-bus distribution network with 2000 EVs, and the SA results are compared with a deterministic technique and particle swarm optimization results.**

***Index Terms*—Demand Response, Electric Vehicle, Energy Resource Management, Simulated Annealing.**

I. Introduction

The successive integration of large amounts of Distributed Energy Resources (DERs), namely Distributed Generation (DG) and the introduction of electricity markets are the reasons of the changes in the power system planning and operation [1, 2]. The integration of DERs would highly benefit from some changes in the traditional power system structure, mainly with a decentralization of the management and control. Over the past years, the smart grid is presented as the most suitable solution to deal with future changes, leading to a better management and control of the power system. Smart grid can be defined as a structure that has the main purpose of integrating different players, technologies and resources that act in this new power system context [3, 4, 5].

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In the smart grid context, Virtual Power Players (VPPs) are important agents, aggregating and managing DERs and negotiating as buyers and/or sellers in electricity markets [6]. The VPP has also the capacity of managing and operating a specific area of an electric network, mainly at the distribution network level. The interest in Electric Vehicles (EVs) is rising in several countries, mainly in Europe, Japan, the United States and China, due to their high dependence of petroleum and concern about Carbon dioxide emissions [7]. It is predicted that most EV models will require an electric network connection with the purpose of fully or partially charging their batteries, but EVs might also have the capability of injecting energy in the network. This ability is commonly referred as Vehicle-to-Grid (V2G). The VPP is a suitable player to aggregate and manage this type of resource [8]. EVs can also bring advantages for the VPP with the capability of controlling the charge and/or discharge process in different periods and in several places.

One of the advantages of EVs is the capability to support the intermittent behaviour of the renewable energy sources (e.g., wind and solar power). The VPP also needs to guarantee an certain amount of energy in the battery of the EV to enable the user's trips for the next periods [8]. In a scenario with high EVs penetration, the load diagram can be changed from the one considered in the present day [8, 9]. Another important aspect in the application of EVs is the possibility of EVs to respond to Demand Response (DR) programs [10, 11]. It is possible to use a DR program for EVs, in order to achieve improvements in the management of resources by the VPP. One of the ideas of DR in EVs is to reduce the minimum energy in the batteries of EVs required by their owners, leading to smooth the impact of EVs into the load diagram [12]. The trip reduce program is one of the programs proposed in [12], which consists in reducing the trip necessity in return of some financial benefits to the EV user. This DR event would help reducing the energy of charging the EV by the VPP. Basically, the VPP can control the charge, discharge and DR for all the aggregated EVs according to the established contracts between the EVs owners and VPP.

In a future scenario, the VPP will aggregate a large amount of DERs in a specific network area. Moreover, this large penetration will turn the Energy Resource Management (ERM) into a large dimension and complex Mixed-Integer Non-Linear Programming (MINLP) problem [13]. Therefore, optimization techniques could take several minutes or even hours to determine the optimal solution. Despite deterministic techniques are recommended to obtain the optimal solution, in this sort of hard and complex problems, Artificial Intelligent (AI) techniques gain more relevance than the deterministic ones [14], because they can ensure a good solution in a the short amount of time. In the AI field, the metaheuristic techniques are appropriated to solve the optimization problems. Metaheuristic techniques search for local optima and include a mechanism based on biological processes to escape from local optimal solution, finding new local optimum [14].

This paper proposes a methodology that is based on the one developed by the same authors in references [8, 15], in which a Simulated Annealing (SA) approach solves the energy resource management considering an intensive use of EVs. The SA approach is adapted to solve the ERM problem with DR programs for EVs. In this paper, the trip reduce program for the EVs was implemented. The VPP can control the charge, discharge and trip reduce program. The SA approach is compared with a deterministic approach and particle swarm optimization presented in reference [12].

The structure of the paper is divided into the following sections: the introduction of the paper is presented in Section I; Section II is related to the concept of the energy resource management in a smart grid context; the proposed simulated annealing technique is explained in Section III; Section IV illustrates the case study implemented in the 32-bus distribution network; and finally, the most relevant conclusions related to this work are presented in the section V.

II. Energy Resource Management

The ERM has the objective of determining the best operation point of the available DERs, considering different objective to obtain the best solution [8]. Typically, it is formulated as the minimization of the operation costs, or minimization of the greenhouse gases emissions or minimization of the active power losses [16]. The traditional power system structure was based on a centralized economic dispatch of large power plants, with unidirectional power flow to the consumers. An economic dispatch is a ERM which obtains the optimal scheduling with a global objective of minimizing the total operation costs of generation units, and it is subjected to supply the demand and to guarantee power system operation constraints [17].

Currently, in a smart grid is required a decentralized ERM of the resources available in the electric network. The ERM should be conducted by several players, including network operators and VPPs. The proposed SA methodology is indicated to be applied by a VPP to determine the ERM of the available resources for the next day. The SA methodology has the objective of minimizing the operation costs of the available DERs for the next day (24 hours of the time horizon). The SA methodology also needs to guarantee the energy supply to the demand of consumers and EV users' requirements. In this paper, the management of resources such as the distributed generation, external suppliers and electric vehicles has been considered.

The proposed SA methodology has to follow a mathematical formulation of the ERM, which has been previously used in other work [12]. The ERM is classified as a Mixed-Integer Non-Linear Programming (MINLP) problem. In reference [12] it can be found a more detailed description of the mathematical formulation used in ERM problems considering an intensive use of EVs. In reference [12] are used two DR programs to the EVs, the trip reduce DR program and the trip shifting DR program. In this paper, it was only considered the trip reduce DR program. The mathematical formulation related to the trip shifting DR program was not considered in the proposed SA methodology. The trip shifting DR program will be further explored in future works with the proposed SA methodology.

A. *Trip Reduce Demand Response Program*

Including the trip reduce DR program in the ERM, the VPP can control the charge, discharge and trip reduction of the available EVs (connected to VPP in distribution network). The idea is to reduce the energy with the expected trip for the next day, giving some remuneration to the EV user in order to reduce its trip. The EV will have to accept the proposal of the VPP to eventually travel a shorter distance with the EV, through a communication structure such as an internet application, an SMS message, etc. If the EV user accepts the possibility of reducing the trip, then the VPP may decrease the charging energy of the EV and help minimizing the operation cost.

III. Simulated Annealing

The simulated annealing algorithm was proposed in 1983 by Kirkpatrick et al. [18, 19]. Since then, the SA algorithm has been used with success to solve hard and complex problems in many applications. In the power system field, the SA was also applied with good results [20]. A detailed explanation on the SA algorithm can be consulted in reference [21], which includes a full description of the cooling process and all parameters used in the SA algorithm.

A. *Proposed Simulated Annealing*

In this paper, the SA algorithm presented in [15] has been applied. The geometric cooling process is used to reduce the temperature value through the iterations of the SA algorithm. The termination criterion is accomplished if the maximum number of iterations is reached, or if the fitness function does not improve during a certain number of iterations.

In this algorithm, several heuristics are used to generate a neighbour solution, instead of the classic approach of generating random movements [22]. Heuristics are used to generate a solution for distributed generations and electric vehicles. In this paper, it has been included a new heuristic to deal with the trip reduce program for EVs.

B. *Trip Reduce Heuristic*

The proposed SA methodology required the inclusion of a heuristic to deal with the trip reduce program for EVs. It has been implemented a heuristic similar to the one presented in other work [12]. The implemented heuristic increases the variables of the trip reduction when the DR program price is lower than the mean generation total cost (considering the DG units and external suppliers) and the EV charge price.

IV. CASE STUDY

The 32-bus distribution network is used to test the proposed simulated annealing methodology. In this network, several DG units have been included taking into account a projection of DG penetration to the year 2040 [23]. The distribution network has an upstream connection represented by bus 0, in which are located the external suppliers that the VPP can negotiate with. In this case study, it is used the same scenario presented in [12], in order to be possible to compare the proposed SA methodology with a deterministic one (designated by MINLP) and a Particle Swarm Optimization (PSO) method.

The case study presents the results for three different scenarios: Smart Charging (SC), Vehicle-to-Grid (V2G) and Trip Reduction (TR). The SC scenario only considers the possibility of the VPP to control the charging process, taking into consideration the trip requirements of the EV user for the next day. The V2G scenario enables the VPP to control charge and discharge process for each EV connected to the network. The TR scenario considers that the VPP can control the charge discharge and trip reduce program.

Section A presents more detailed information on the resources used in this case study. Section B shows the parameterization and results of the proposed SA approach. Section C depicts the comparison between the SA, MINLP and PSO results.

A. *Scenario Characterization*

In the distribution network are considered 66 DG units divided into: 32 photovoltaic units, 5 wind units, 15 combined heat and power units, 3 biomass units, 2 municipal solid waste units, 2 hydro units and 7 fuel cell units. 10 external suppliers are also considered to an upstream connection located in bus 0 of the distribution network. More detailed information on the resources used in this network can be seen in [12].

2000 EVs moving around the distribution network are considered. This EVs penetration is acceptable for the year 2040, regarding the dimension of the 32-bus distribution network. The EVs trip pattern is the same used in a previous work [12]. The EVs trip pattern was based on the U.S. national travelling report of 2009 [24].

B. *Parameterization and Results of proposed SA*

Table I shows the SA parameters values used for the different scenarios of the case study. It has been made a sensitivity analysis to determine the right values for all parameters used in the proposed SA approach. The proposed SA approach has been run several times with different parameter values until the SA algorithm obtained a constant low value for the fitness function. For each parameter value, the SA approach has been run 100 times in order to establish if the parameter value was suitable to the case study.

TABLE I. PARAMETERS USED IN SA APPROACH

Parameters	Case study scenarios		
	SC	V2G	TR
Initial temperature	2500	3000	3000
Cooling rate	0.85	0.90	0.90
Maximum number of iterations	60	60	60
Iterations at same temperature	6	6	6
Fitness improvement threshold	5.10^{-4}	5.10^{-4}	5.10^{-4}
Maximum number of iterations without fitness improvement	20	20	20

Table II presents the results of the proposed SA approach for a total of 1000 runs for the three scenarios. In this table are indicated the best, worst, mean solutions and Standard Deviations (STD) over 1000 runs. The mean execution time for the three scenarios is also presented.

TABLE II. RESULTS OF THE SA METHODOLOGY

Scenario	Operation cost (m.u.)				Mean time (s)
	Best	Worst	Mean	STD	
SC	8924.33	8967.20	8944.68	6.47	14.10
V2G	8533.87	8556.04	8545.85	3.42	11.49
(TR	8068.61	8099.87	8086.75	4.95	13.90

The robustness test using 1000 runs demonstrated a good behaviour of the SA methodology for the three scenarios. It did not verify any violation during the 1000 trials of the SA methodology. In order to verify any violation, each constraint of the ERM problem is checked for each solution. The SA methodology presents a low execution time in all scenarios, in which the SC scenario presents the maximum time of 14.10 seconds. It is also important to analyse the very low standard deviation presented in the three scenarios.

Figure 1 depicts the objective function evolution by iterations of the SA methodology for the TR scenario. The SA methodology demonstrated a fast convergence in this scenario. A fast SA convergence helps the VPP finding a good solution in a short time and testing several case studies with the SA approach. In the other two scenarios, the SA methodology presented a similar behaviour in terms of a quick convergence.

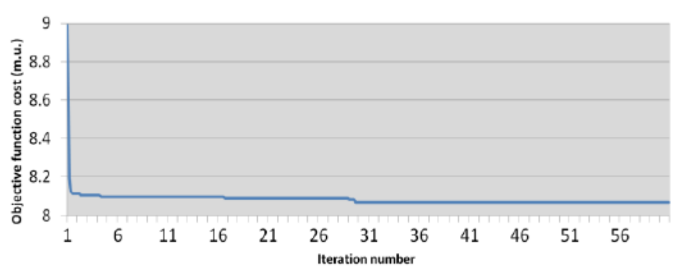

Figure 1. Objective function evolution by iteration of the SA methodology.

Figure 2 presents the resulting load diagram for the V2G scenario. In Figure 2, are represented consumers (blue bars), EVs charges (green bars) and the system demand (blue line). The system demand considers the consumers' demand, EVs charges and EVs discharges.

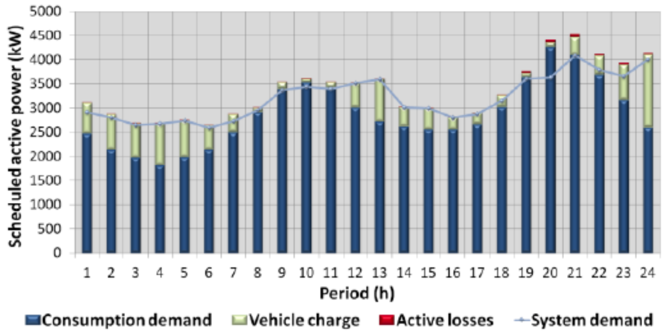

Figure 2. Load diagram of SA methodology for the V2G scenario.

The resulting load diagram for the TR scenario considering the consumers' demand (represented by blue bars) and the EVs charges (green bars) is illustrated in Figure 3. The VPP manages intelligently the charge of EVs to schedule in periods with resources' costs lower than in the other periods. Therefore, the EVs charge is more concentrated in night periods in order to avoid the charging in peak periods. In the peak periods, the VPP uses the EVs discharge instead of scheduling resources that are more expensive. The EVs discharge also helps reducing the system demand in peak periods, as it can be seen in Figure 3.

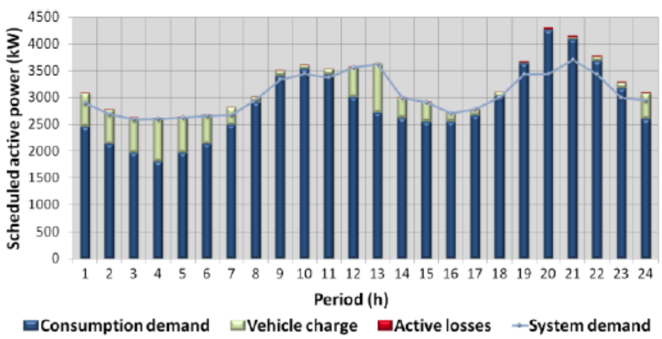

Figure 3. Load diagram of SA methodology for the TR scenario.

In comparison between Figures 2 and 3, it is possible to conclude that the trip reduction helps the VPP reducing the EVs charges in the night periods. It also helps the VPP avoiding unnecessary charges in the peak periods that appear in Figure 2. These charges occurred to guarantee at least 30% of the battery's capacity in all EVs at the end of the day. In Figure 3, it is not necessary to charge more the EVs in order to achieve the same requirement at the end of 24 hours. The trip reduction also helps using more EVs discharges in the peak periods, reducing the system demand value in these periods.

Figure 4 shows the energy resource scheduling for the TR scenario. In this figure, the scheduling per type of resource is presented. The EVs discharge appears with intensity in the peak periods, mainly in periods 20 and 21. This fact helps the VPP decreasing the operation cost of the energy resource scheduling.

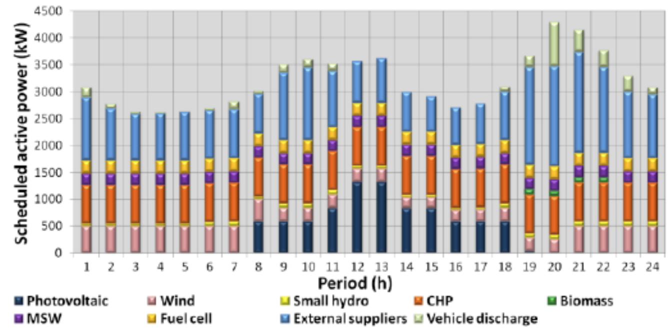

Figure 4. Energy resource scehduling of SA methodology.

The trips energy consumption for the TR scenario considering the use of trip reduction DR program is presented in Figure 5. In this scenario, EVs respond positively to the VPP with a reduction of 50 % in the expected trip. This 50 % reduction is illustrated by a red area in Figure 5. The resulting trip of the vehicles is indicated in the blue area.

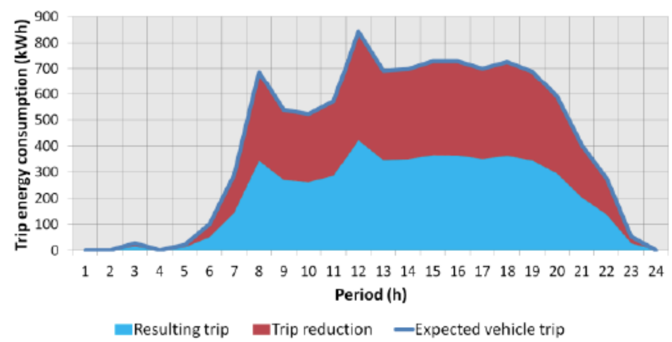

Figure 5. Energy consumption with trips for the trip reduction scenario.

C. *Comparison of the proposed SA with MINLP and PSO*

The proposed SA results are compared with the one obtained by MINLP and PSO in [12]. The comparison in terms of operation cost and mean time is illustrated in Table III.

TABLE III. COMPARISON OF SA RESULTS WITH MINLP AND PSO

Scenario	Operation cost (m.u.)			Mean time (s)		
	SA	MINLP	PSO	SA	MINLP	PSO
SC	8924.33	8350.23	8408.68	14.10	85,475	30.99
V2G	8533.87	8177.47	8219.66	11.49	89,748	31.98
TR	8068.61	7627.97	7887.03	13.90	95,657	33.19

In the SC scenario, the difference between the SA and MINLP methodologies is of 6.4%, and between the SA and PSO methodologies is around 5.8 %. In the V2G scenario, the operation cost difference is about 4.2 % between the SA and MINLP and 3.7 % between the SA and PSO. In the TR scenario, the difference in terms of operation cost between the SA and MINLP is approximately of 5.5 % and between the SA and PSO is 2.3 %.

In what concerns the execution time, the SA approach presents the lowest execution time result, and the MINLP approach presented a time higher than 24 hours for the three scenarios. In the SC scenario, the SA approach found a solution in 14.10 seconds, the MINLP approach found it in 85,475 seconds (around 23.74 hours), and PSO found a solution in 30.99 seconds. In the V2G scenario, the SA, MINLP and PSO approaches presented 11.49, 89,748 (around 24.93 hours) and 31.98 seconds respectively. In the TR scenario, the SA approach presented 13.90 seconds, the MINLP approach presented 95,657 seconds (around 26.57 hours) and the PSO approach presented 33.19 seconds.

Considering that VPP will require an ERM for the next day, the MINLP cannot be used as a suitable methodology to solve the ERM solution. In the SC scenario, the SA is around 6062 times faster than the MINLP, and it is approximately 2 times faster than the PSO. In the V2G scenario, the SA is around 7811 and 2.8 times faster than the MINLP and PSO methodologies, respectively. In TR scenario, the SA is 6882 and 2.4 times faster than the MINLP and PSO methodologies, respectively.

The operation cost results of the SA methodology are not encouraging to the energy resource management by the VPP, but it is also important to consider the execution time as a relevant aspect to analyze the performance of the three methodologies. This aspect has influence in the VPP management of DERs, because the VPP may have to test several scenarios with different consumers' demand and EVs trip requirements. The SA approach can solve each scenario in a low execution time without losing a significant solution quality. The MINLP approach (deterministic methodology) is not suitable to the three scenarios, because it cannot present the optimal solution in less than a day. On the other hand, the SA is suitable to solve the ERM problem for the VPP, presenting a good solution in a significant short time. The SA approach presents a worse solution than the PSO approach, but it takes less time than the PSO to find a solution. The SA methodology is also a valid method for the VPP, in order to find good solution in a low time. It could be also used as an initial solution to the PSO methodology, and then the PSO would improve a good initial solution. The SA approach can be also used for other types of VPP management with the objective of finding a valid solution in a short execution time, such as multi-objective ERM problems and stochastic ERM problems.

Figure 6 indicates the energy resource scheduling of the SA, MINLP and PSO methodologies for the three scenarios.

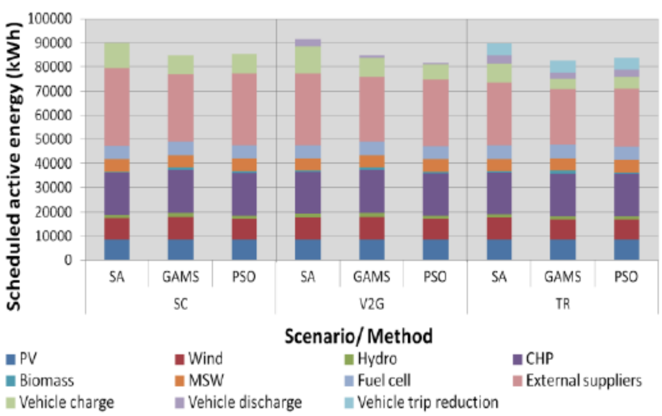

Figure 6. Energy resource scehduling of SA methodology.

In the three scenarios, the SA presents the highest energy value of the three methodologies, leading to a high operation cost.

The charge and discharge profile for the three scenarios is presented in Figure 7. The SA approach applies more charges and discharges than the MINLP and PSO approaches. The greater use of charge and discharge process is one of the reasons for the highest operation cost, comparing to the other two scenarios.

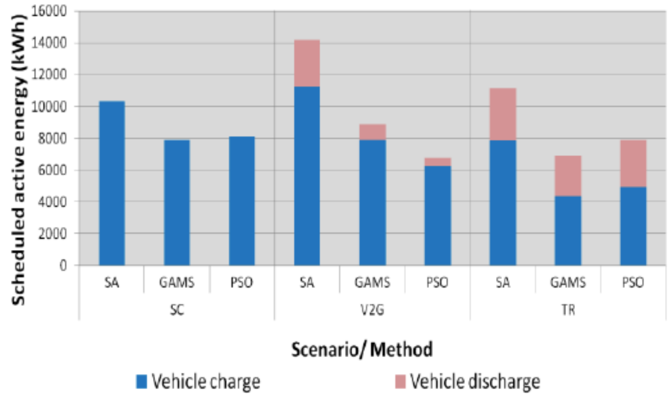

Figure 7. Charge and discharge profile for the three scenarios.

V. CONCLUSIONS

An intensive use of DERs, including EVs, in the smart grid implies more complexity to the management of the electric network. In this scenario, the ERM exponentially increases the execution time to find the optimal solution. It is necessary to use adequate optimization techniques to solve this type of problem. The computational intelligence field can help dealing with a hard and complex problem, presenting good solutions in a low execution time. A SA approach is adapted to solve a complex ERM problem with a large penetration of EVs for the next day.

In this paper, it is considered a new option to control EVs, and the use of DR programs can significantly help the management of EVs by the VPP. The trip reduce DR program has been implemented. In the case study, it is proved the advantage of this sort of DR program with a significant reduction in the operation cost. In the V2G scenario, the MINLP approach presents an operation cost of 8177.47 m.u. In the TR scenario, the same approach obtains a solution of 7627.97 m.u. The use of the DR program leads to a saving in the operation costs of approximately 6.7 %.

The SA methodology solves the ERM problem in a shorter execution time than the other two approaches (MINLP and PSO). However, the SA approach presented operation cost results that are a slightly higher than the ones presented by MINLP and PSO approaches. In V2G scenario, the SA is approximately 7811 and 2.8 times faster than the MINLP and PSO approaches, respectively. The inclusion of more DERs can lead to an exponential increase of the execution time. Therefore, the SA approach can be a valid method to present a good solution in a very low execution time for more complex ERM problems.

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